

VAR modeling illustration with real data

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The following material is taken from Fan & Yao (2015).

1 VAR Modeling

Let x be the matrix with 3 columns containing the log daily returns in 2011 of FTSE 100, FTSE MidCap, FTSE SmallCap. To fit a vector VAR(p) model with p determined by BIC (i.e. the Schwartz Criterion), we issue the following commands and obtain the summary of fitted results:

```
mydata = read.table("~/ftse2011.dat",header = T)
tt = nrow(mydata)
mydata2 <- mydata[tt:1,]
x1 = diff(log(mydata2[,2]))
x2 = diff(log(mydata2[,3]))
x3 = diff(log(mydata2[,4]))
x = data.frame(x1,x2,x3)
names(x)=c("FTSE100", "FTSE MidCap", "FTSE SmallCap")
attach(x)
library(vars)
FTSEvar = VAR(x, lag.max =3, ic="SC")
summary(FTSEvar)

##
## VAR Estimation Results:
## =====
## Endogenous variables: FTSE100, FTSE.MidCap, FTSE.SmallCap
## Deterministic variables: const
## Sample size: 248
## Log Likelihood: 2748.593
## Roots of the characteristic polynomial:
## 0.1363 0.1363 0.04969
## Call:
## VAR(y = x, lag.max = 3, ic = "SC")
```

```

##
##
## Estimation results for equation FTSE100:
## =====
## FTSE100 = FTSE100.l1 + FTSE.MidCap.l1 + FTSE.SmallCap.l1 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## FTSE100.l1      0.4623839   0.1822584    2.537   0.0118 *
## FTSE.MidCap.l1  -0.5277461   0.2154000   -2.450   0.0150 *
## FTSE.SmallCap.l1 0.2438484   0.1981300    1.231   0.2196
## const          -0.0003319   0.0008497   -0.391   0.6964
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01329 on 244 degrees of freedom
## Multiple R-Squared: 0.03624, Adjusted R-squared: 0.02439
## F-statistic: 3.058 on 3 and 244 DF, p-value: 0.02896
##
##
## Estimation results for equation FTSE.MidCap:
## =====
## FTSE.MidCap = FTSE100.l1 + FTSE.MidCap.l1 + FTSE.SmallCap.l1 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## FTSE100.l1      0.6041161   0.1689675    3.575 0.000422 ***
## FTSE.MidCap.l1  -0.5709383   0.1996923   -2.859 0.004616 **
## FTSE.SmallCap.l1 0.2651595   0.1836817    1.444 0.150139
## const          -0.0005873   0.0007877   -0.746 0.456663
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01232 on 244 degrees of freedom
## Multiple R-Squared: 0.08665, Adjusted R-squared: 0.07542
## F-statistic: 7.716 on 3 and 244 DF, p-value: 6.044e-05
##
##
## Estimation results for equation FTSE.SmallCap:
## =====
## FTSE.SmallCap = FTSE100.l1 + FTSE.MidCap.l1 + FTSE.SmallCap.l1 + const
##
##           Estimate Std. Error t value Pr(>|t|)
## FTSE100.l1      0.2692036   0.1076958    2.500   0.0131 *
## FTSE.MidCap.l1  -0.1276323   0.1272791   -1.003   0.3170

```

```
## FTSE.SmallCap.l1  0.0778511  0.1170743  0.665  0.5067
## const            -0.0006338  0.0005021  -1.262  0.2080
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.007855 on 244 degrees of freedom
## Multiple R-Squared:  0.1037, Adjusted R-squared:  0.09271
## F-statistic: 9.414 on 3 and 244 DF,  p-value: 6.557e-06
##
##
## Covariance matrix of residuals:
##              FTSE100 FTSE.MidCap FTSE.SmallCap
## FTSE100      1.767e-04  1.545e-04  8.617e-05
## FTSE.MidCap  1.545e-04  1.519e-04  8.237e-05
## FTSE.SmallCap 8.617e-05  8.237e-05  6.170e-05
##
## Correlation matrix of residuals:
##              FTSE100 FTSE.MidCap FTSE.SmallCap
## FTSE100      1.0000      0.9430      0.8252
## FTSE.MidCap  0.9430      1.0000      0.8508
## FTSE.SmallCap 0.8252      0.8508      1.0000
```

The selected order by BIC is $p = 1$. From the previous fitting result, we find that some coefficient estimates are insignificant. To refit the model by leaving out insignificant terms, we use

```
FTSEvarR = restrict(FTSEvar)
summary(FTSEvarR)

##
## VAR Estimation Results:
## =====
## Endogenous variables: FTSE100, FTSE.MidCap, FTSE.SmallCap
## Deterministic variables: const
## Sample size: 248
## Log Likelihood: 2744.399
## Roots of the characteristic polynomial:
## 0.2057 0.2057      0
## Call:
## VAR(y = x, lag.max = 3, ic = "SC")
##
##
## Estimation results for equation FTSE100:
## =====
```

```

## FTSE100 = FTSE100.l1 + FTSE.MidCap.l1
##
##               Estimate Std. Error t value Pr(>|t|)
## FTSE100.l1      0.4689      0.1816   2.582   0.0104 *
## FTSE.MidCap.l1 -0.3983      0.1904  -2.092   0.0375 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01329 on 246 degrees of freedom
## Multiple R-Squared: 0.02987, Adjusted R-squared: 0.02198
## F-statistic: 3.787 on 2 and 246 DF, p-value: 0.02399
##
##
## Estimation results for equation FTSE.MidCap:
## =====
## FTSE.MidCap = FTSE100.l1 + FTSE.MidCap.l1
##
##               Estimate Std. Error t value Pr(>|t|)
## FTSE100.l1      0.6083      0.1687   3.605 0.000378 ***
## FTSE.MidCap.l1 -0.4265      0.1769  -2.411 0.016634 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01235 on 246 degrees of freedom
## Multiple R-Squared: 0.0782, Adjusted R-squared: 0.07071
## F-statistic: 10.43 on 2 and 246 DF, p-value: 4.469e-05
##
##
## Estimation results for equation FTSE.SmallCap:
## =====
## FTSE.SmallCap = FTSE100.l1
##
##               Estimate Std. Error t value Pr(>|t|)
## FTSE100.l1  0.19508      0.03714   5.253 3.24e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.00785 on 247 degrees of freedom
## Multiple R-Squared: 0.1005, Adjusted R-squared: 0.09684
## F-statistic: 27.59 on 1 and 247 DF, p-value: 3.236e-07
##
##

```

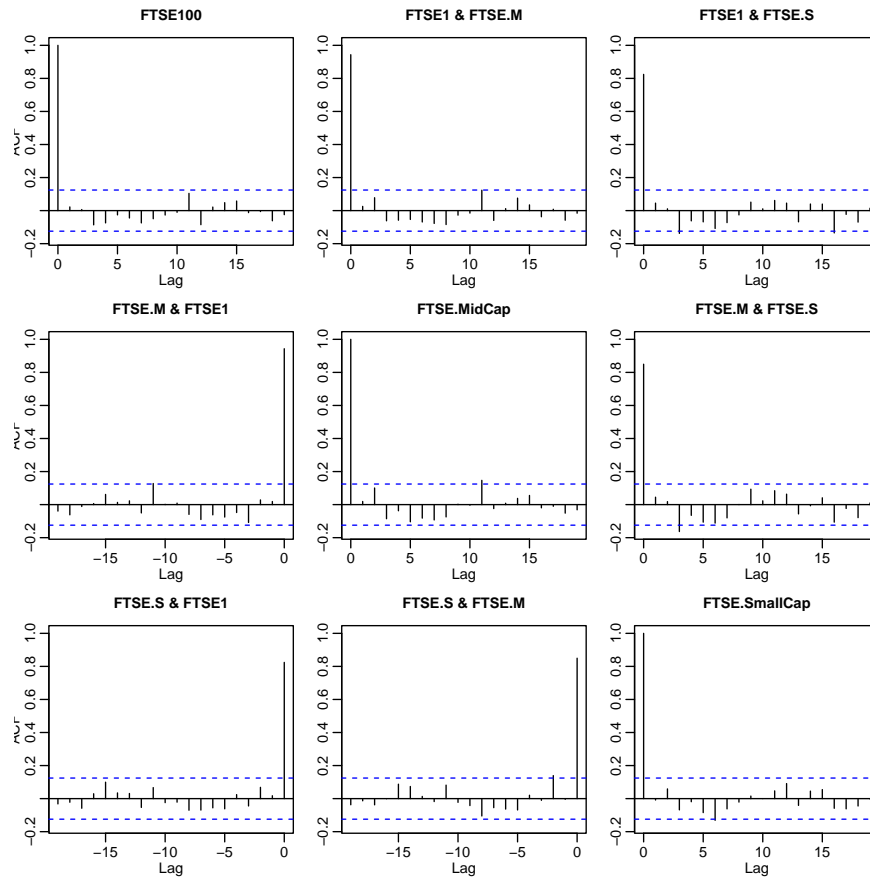
```
##
## Covariance matrix of residuals:
##           FTSE100 FTSE.MidCap FTSE.SmallCap
## FTSE100      1.778e-04  1.557e-04  8.653e-05
## FTSE.MidCap  1.557e-04  1.532e-04  8.277e-05
## FTSE.SmallCap 8.653e-05  8.277e-05  6.197e-05
##
## Correlation matrix of residuals:
##           FTSE100 FTSE.MidCap FTSE.SmallCap
## FTSE100      1.0000      0.9433      0.8243
## FTSE.MidCap  0.9433      1.0000      0.8495
## FTSE.SmallCap 0.8243      0.8495      1.0000
```

which leads to

$$\begin{aligned} \text{FTSE100}_t &= 0.469\text{FTSE100}_{t-1} - 0.398\text{FTSEMid}_{t-1} + \varepsilon_{t1}, \\ \text{FTSEMid}_t &= 0.608\text{FTSE100}_{t-1} - 0.427\text{FTSEMid}_{t-1} + \varepsilon_{t2} \\ \text{FTSESmall}_t &= 0.195\text{FTSE100}_{t-1} + \varepsilon_{t3}. \end{aligned}$$

The following figure presents the cross-correlations of the residuals from the above fitted VAR(1) model, produced by R command

```
acf(residuals(FTSEvarR))
```



More diagnostic plots can be produced by calling the following R functions:

```
FTSEdiag = serial.test(FTSEvarR)
plot(FTSEdiag)
```

To perform the $Q_k(m)$ test for the residual with, for example, $m = 6$, run

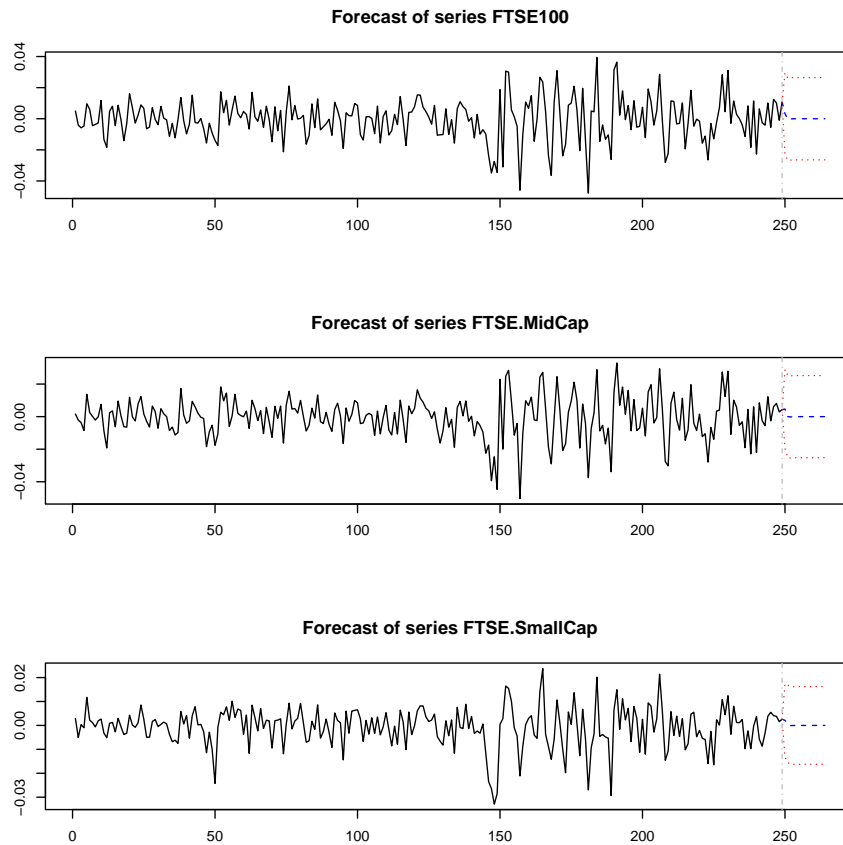
```
serial.test(FTSEvarR, lags.pt = 6, type = "PT.adjusted")

##
## Portmanteau Test (adjusted)
##
## data: Residuals of VAR object FTSEvarR
## Chi-squared = 81.537, df = 45, p-value = 0.0006984
```

VAR models can be used to forecast future values. For example, we may forecast the next 15 returns of those three FTSE indices by using R function

`predict` as follow, where we specify the predictive boundaries with the coverage probability 0.95.

```
FTSEpred = predict(FTSEvarR,n.ahead = 15,ci=0.95)
plot(FTSEpred)
```



2 Granger Causality

The function `causality` in the package `vars` implements the Granger Causality analysis.

```
causality(FTSEvarR,cause="FTSE100")
# causality(FTSEvarR,cause="FTSE100",boot = TRUE,boot.runs = 1000)

## $Granger
```

```
##
## Granger causality H0: FTSE100 do not Granger-cause FTSE.MidCap
## FTSE.SmallCap
##
## data:  VAR object FTSEvarR
## F-Test = 4.7663, df1 = 2, df2 = 732, p-value = 0.008778
##
##
## $Instant
##
## H0: No instantaneous causality between: FTSE100 and FTSE.MidCap
## FTSE.SmallCap
##
## data:  VAR object FTSEvarR
## Chi-squared = 116.87, df = 2, p-value < 2.2e-16
```

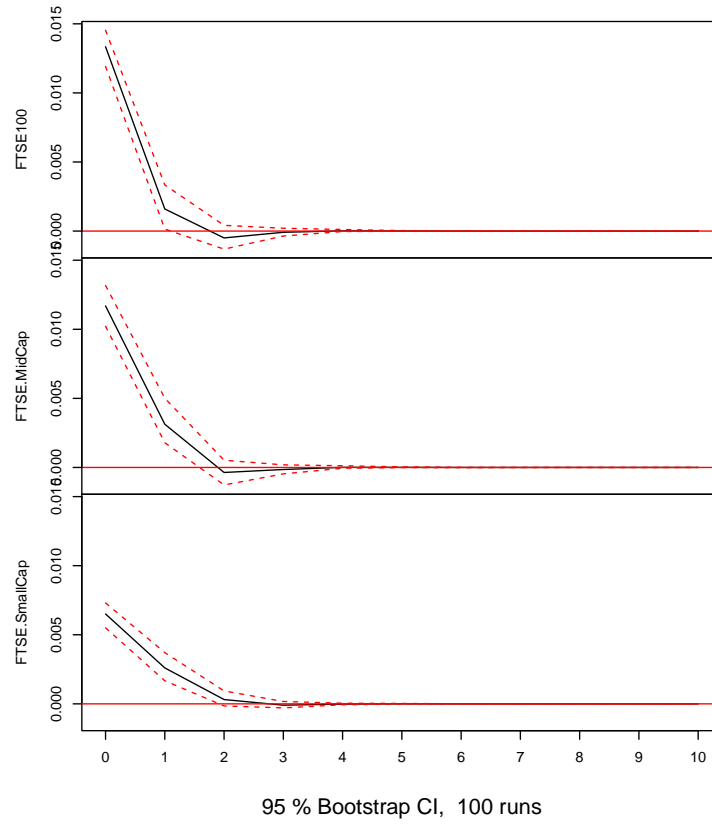
The null hypothesis of no Granger causality is rejected with the p -value 0.001, there is significant evidence indicating that FTSE100 Granger causes FTSE MidCap and FTSE SmallCap. The null hypothesis of no instantaneous causality is rejected with the p -value 0.

3 Impulse Response Functions

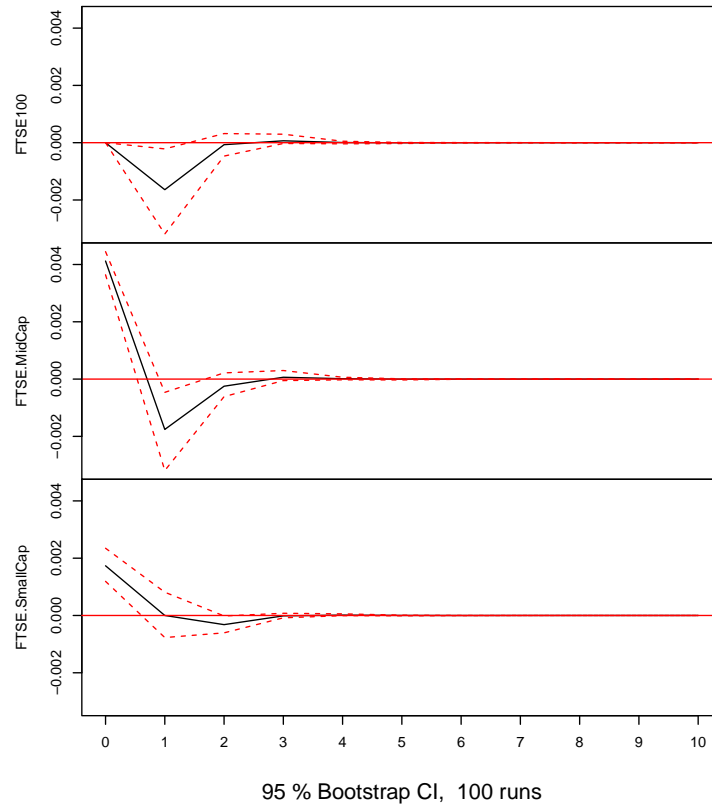
The effect of a change in one component series on the other components can be investigated via the so-called **impulse response functions**, which measure the resulting changes in other components at different time lags due to a unit change in one component series.

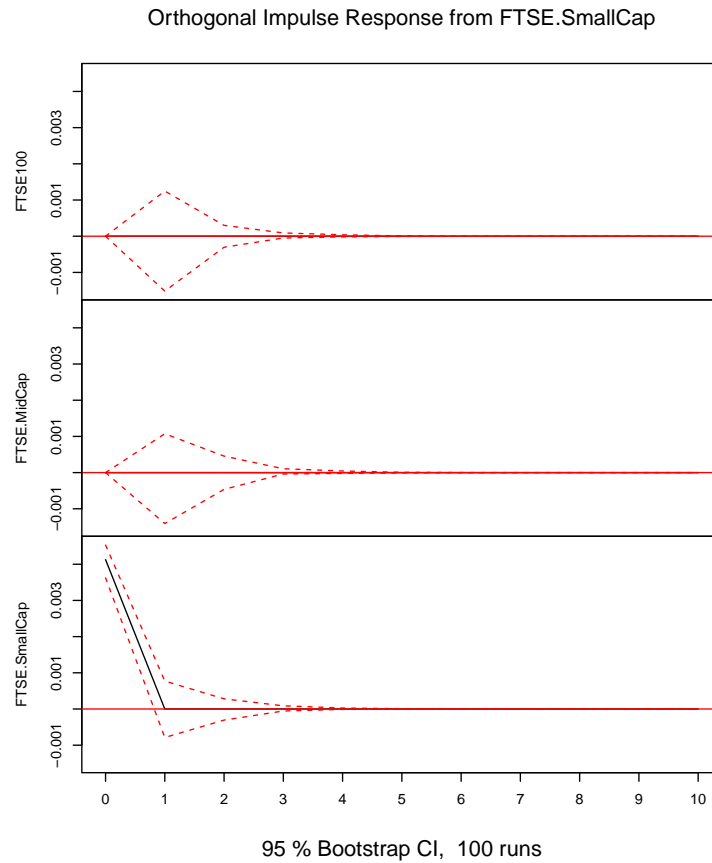
```
irfFTSE = irf(FTSEvarR)
plot(irfFTSE)
```


Orthogonal Impulse Response from FTSE100



Orthogonal Impulse Response from FTSE.MidCap





4 Forecast Error Variance Decomposition

In variance decomposition, the forecast error variance is decomposed into components accounted for by innovations in the different variables of the system. The function `fevd` in the package `vars` implements the Forecast Error Variance Decomposition analysis.

```
fevd(FTSEvar)

## $FTSE100
##          FTSE100 FTSE.MidCap FTSE.SmallCap
## [1,] 1.0000000  0.00000000  0.000000000
## [2,] 0.9779315  0.01663722  0.005431299
## [3,] 0.9778880  0.01667701  0.005434949
```

```

## [4,] 0.9778843 0.01667973 0.005435924
## [5,] 0.9778843 0.01667980 0.005435941
## [6,] 0.9778843 0.01667980 0.005435941
## [7,] 0.9778843 0.01667980 0.005435941
## [8,] 0.9778843 0.01667980 0.005435941
## [9,] 0.9778843 0.01667980 0.005435941
## [10,] 0.9778843 0.01667980 0.005435941
##
## $FTSE.MidCap
##      FTSE100 FTSE.MidCap FTSE.SmallCap
## [1,] 0.8892089 0.1107911 0.000000000
## [2,] 0.8703408 0.1225813 0.007077877
## [3,] 0.8702947 0.1226010 0.007104352
## [4,] 0.8702878 0.1226060 0.007106174
## [5,] 0.8702878 0.1226060 0.007106174
## [6,] 0.8702878 0.1226060 0.007106175
## [7,] 0.8702878 0.1226060 0.007106175
## [8,] 0.8702878 0.1226060 0.007106175
## [9,] 0.8702878 0.1226060 0.007106175
## [10,] 0.8702878 0.1226060 0.007106175
##
## $FTSE.SmallCap
##      FTSE100 FTSE.MidCap FTSE.SmallCap
## [1,] 0.6809012 0.04774647 0.2713524
## [2,] 0.7097809 0.04508592 0.2451332
## [3,] 0.7090695 0.04596916 0.2449613
## [4,] 0.7090733 0.04597134 0.2449554
## [5,] 0.7090732 0.04597146 0.2449554
## [6,] 0.7090732 0.04597146 0.2449554
## [7,] 0.7090732 0.04597146 0.2449554
## [8,] 0.7090732 0.04597146 0.2449554
## [9,] 0.7090732 0.04597146 0.2449554
## [10,] 0.7090732 0.04597146 0.2449554

```